Data Management

Examining the Data

- Look at some random inputs
- Look at the largest and smallest inputs (by file size)
  - These are the most likely to be weird or corrupted

Small file

- Manually solve the task

Splitting

- Training set – used by SGD to learn model parameters
- Validation set – used by us to learn hyperparameters
- Test set – used once to measure final model performance

Overfitting

- Goal: Learn to classify *unseen* images
- Optimization objective: Learn to classify *training set* images

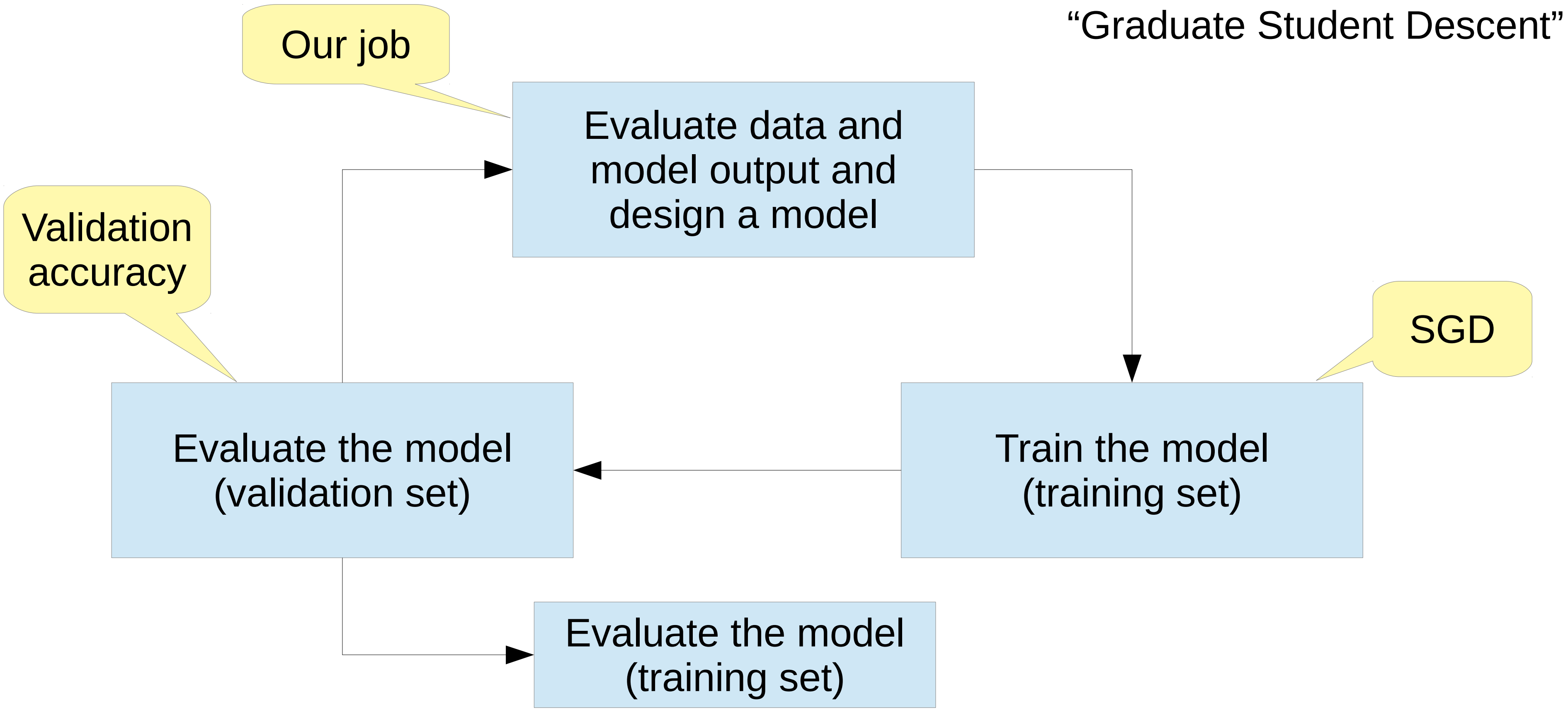
Training set (60-80% of data)
Model parameters overfit by SGD

Validation (10-20%)
Hyperparameters overfit by us

Test (10-20%)
Not used in training, not overfit

Be sure to split randomly

Tuning



Our job
"Graduate Student Descent"
Evaluate data and model output and design a model
Validation accuracy
SGD
Evaluate the model (validation set)
Train the model (training set)
Evaluate the model (training set)

Initialization

Initialization – All Zero

$x = ???$ | $g_1 = 0$

Linear 1

$v_1 = W_1 x$

$g_1 = W_1^T g_2$

$\nabla_{W_1} \ell(v_3) = g_2 x^T$

$v_1 = 0$ | $g_2 = 0$ | 0

ReLU

$v_2 = \max(v_1, 0)$

$g_2 = g_3 [v_1 > 0]$

$v_2 = 0$ | $g_3 = 0$

Linear 2

$v_3 = W_2 v_2$

$g_3 = W_2^T g_o$

$\nabla_{W_2} \ell(v_3) = g_o v_2^T$

$v_3 = 0$ | $g_o = ???$ | 0

$$g_o = \nabla_{v_3} \ell(v_3)$$

Initialization – Random

Normal distribution

$$W_i \sim N(\mu_i, \sigma_i^2)$$

Means

Standard deviations

In practice, the mean is zero and we need to choose a standard deviation

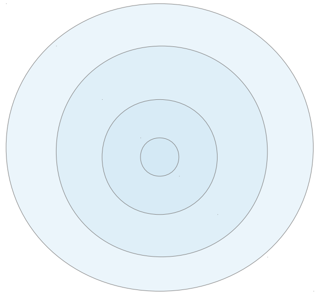
Initialization – Scaling

$$o = W_2 W_1 x$$

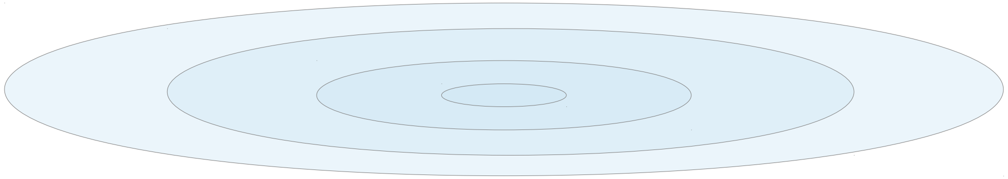
$$\nabla_{W_1} \ell(o) = \left(W_2^T \left(\nabla_o \ell(o) \right) \right) x^T$$

$$\nabla_{W_2} \ell(o) = \left(\nabla_o \ell(o) \right) \left(W_1 x \right)^T$$

$$\|W_1\| \approx \|W_2\|$$



$$\|W_1\| \gg \|W_2\|$$



Choosing a Standard Deviation

Math

(See the supplementary material for details)

Kaiming Initialization

- Choose either activations or gradients and keep the magnitude roughly constant:
  - Activations: $$W \sim N\left(0, \frac{2}{n_{\mathrm{in}}}\right)$$
  - Gradients: $$W \sim N\left(0, \frac{2}{n_{\mathrm{out}}}\right)$$

Xavier Initialization

- Keep both activation and gradient magnitudes roughly constant throughout the network

$$W \sim N\left(0, \frac{4}{n_{\text{in}} + n_{\text{out}}}\right)$$

In Practice

- The PyTorch defaults are usually good enough.

- The last layer can be initialized to zero.
  - If the previous layers are not zero, the last activation is not zero, so we still get gradients.